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Achievement Goal Orientation Profiles and Performance in a Programming MOOC

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ABSTRACT

It has been suggested that performance goals focused on appearing talented (appearance goals) and those focused on outperforming others (normative goals) have different consequences, for example, regarding performance. Accordingly, applying this distinction into appearance and normative goals alongside mastery goals, this study explores what kinds of achievement goal orientation profiles are identified among over 2000 students participating in an introductory programming MOOC. Using Two-Step cluster analysis, five distinct motivational profiles are identified. Course performance and demographics of students with different goal orientation profiles are mostly similar. Students with Combined Mastery and Performance Goals perform slightly better than students with Low Goals. The observations are largely in line with previous studies conducted in different contexts. The differentiation of appearance and normative performance goals seemed to yield meaningful motivational profiles, but further studies are needed to establish their relevance and investigate whether this information can be used to improve teaching.

CCS CONCEPTS

• **Applied computing → E-learning**.

KEYWORDS

Achievement Goal Orientation, Performance, CS1, MOOC

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1 INTRODUCTION

Motivation is the key force that drives students to seek new knowledge and learn [25, 27]. Motivational strivings are multiple and whereas some students may have goals related to high grades, outperforming others or appearing competent, others may strive for intrinsic objectives such as mastering the topic at hand. Achievement goal orientation is one of the most prominent constructs used to study these achievement-related motivational factors in various learning and achievement settings. Achievement goal orientations describe students' tendency to prefer certain types of goals and outcomes over some others in achievement-related settings [24].

Achievement goal orientations are typically divided between mastery and performance goals (e.g., [6, 23]). Mastery goals refer to an aim to develop competence, whereas performance goals refer to an aim to outperform peers or demonstrate competence. While these two types of goals still remain as the core and basis for a variety of achievement goal frameworks, the modern view on motivational factors has expanded this dichotomous scheme and includes further refinements.

Methodologically achievement goal orientation research can be divided between variable- and person-oriented approaches. While variable-oriented approach focuses on the relations between achievement goal orientation variables (i.e., dimensions of achievement goal orientations) and learning-related outcomes (e.g., performance, interest, or well-being), person-oriented approach [3] focuses on combinations of variables and extracts groups of students who display similar combinations of achievement goal orientations.

Most of the previous applications of achievement goal orientation theory in computing education research rely on the variable-oriented approach (e.g., [40–42]), with only few studies exploring achievement goal orientation profiles. However, for example, Hakulinen and Auvinen [13] have applied the person-oriented approach to identify student profiles in an online data-structures and algorithms course, and used this information to understand how achievement-badges suit different student profiles.

In this study, we adopted the same achievement goal orientation framework Zingaro et al. [41] have used in the context of introductory programming education. In contrast to these previous studies, we used the person-oriented approach and, first, explored what kinds of achievement goal orientation profiles can be identified among students participating in a programming MOOC (**RQ1**) and, second, investigated whether students with different achievement goal orientation profiles differ with respect to their course performance (**RQ2**). Improved understanding of the student population (i.e., what patterns of achievement goal orientations students show and how big a proportion of students show a particular pattern) may have implications on planning of teaching and learning.

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2 BACKGROUND

2.1 Achievement Goal Orientation Dimensions

The dichotomous (i.e., mastery vs. performance) achievement goal framework has seen many extensions over the years, the distinction between performance-approach (demonstrating competence) and performance-avoidance goals (avoiding the demonstration of incompetence) [7, 8] being probably one of the widest spread of them. Mastery-avoidance goals (i.e., avoiding misunderstanding or failing to learn) came along soon after (2 × 2 framework [9]). Both performance-avoidance and mastery-avoidance goals have been proven maladaptive in terms of performance [2, 16] and are also related to a range of other negative effects, such as fear of failure, low self-determination [9] and low help seeking behavior [2].

Hulleman, Senko et al. [16, 29, 31] have further suggested that there is a need to distinguish between performance goals focused on appearing talented (appearance goals) and those focused on outperforming others (normative goals). Springing from different ideas of success, these two types of performance goals are related to different outcomes: performance-approach scales consisting of mostly normative goal items correlated positively with achievement and scales with an emphasis on appearance goal items correlated negatively with achievement.

2.2 Profiles and Academic Achievement

There is already a large number of studies utilizing a person-oriented approach and examining students' achievement goal orientation profiles in various educational contexts (e.g., K12, and higher education). Although the number and nature of the identified profiles in each study naturally depend partly on, for example, the achievement goal measures used and the sample characteristics, some generalizations can still be drawn. It seems that the number of identified goal profiles has varied mainly between three and six with slightly fewer profiles (most commonly three) often identified among younger (e.g., elementary school) students and somewhat more profiles found among older (e.g., university) students (see Niemivirta et al. [24]). Moreover, certain profiles tend to occur across studies. Most common profiles seem to be a predominantly mastery goal profile, a predominantly performance goal profile, and a combined mastery and performance goal profile as well as profiles with moderate and low levels of achievement goals.

There has been debate in achievement goal literature over the benefits of endorsing mastery goals versus combined mastery and performance goals [32]. The empirical findings have been threefold in demonstrating that the mastery-oriented students have the highest academic achievement (e.g. [11]), that students holding both mastery and performance-approach goals display the highest academic achievement (e.g. [34]), or that these two groups perform equally well (e.g. [4, 26]). In addition, it has been shown that predominantly performance goal profile has been linked with moderate achievement, whereas average and low goal profiles with relatively poor academic achievement (e.g. [4, 34]). Variation in these results have also been related to the contextual differences, for example, by stating that mastery goals may be harmful if the tasks (e.g., graded assignments) are closed rather than open-ended [30]. This is especially interesting as automatically assessed programming assignments are often closed by their very nature [12]. Nevertheless, it is important to note that some studies have not found notable differences in performance or academic achievement between goal orientation profiles (e.g. [28]).

2.3 Achievement Goal Orientations in Computing Education

In the context of learning programming, Zingaro et. al have studied achievement goals in relation to performance, enjoyment and post-course interest in three subsequent studies [40–42]. The first study from 2015 focused on mastery and performance goals (without the normative vs. appearance separation) [40]. Findings of this study indicate that while mastery goals are related to good exam performance (r=.19), performance goals may have negative consequences (r=-.3). The follow up study from 2016 [42] introduced the normative and appearance separation and was not able to replicate any of the previous correlations between (normative or appearance) performance goals, mastery goals and exam performance. In multiple regression model, however, mastery goals were still significant and related to increased exam performance. While normative and appearance performance goals were not significant, their interaction was. This examination of the interactions is an interesting step towards person-oriented approach. Finally, replication study from 2018 involved six institutions in four countries [41]. Results varied between institutions, indicating importance of the context.

Interestingly, the interaction of the two performance-approach goal components appeared to result in opposite performance outcomes [exam grade] depending on the study. The earlier study [42] found that adopting only normative or appearance goals was adaptive while striving for both or neither of the goals was maladaptive. The later follow up study, in turn, found that in one of the six institutions either high or low scores in both goals were almost equally beneficial [41].

The research on achievement goal orientations in computing education comprises also studies conducted in other contexts. For example, visualizations of learning behavior and achievement badges have had a different impact on students depending on their achievement goals [1, 13, 18]. In addition, students with different achievement goals were observed to have little or no differences in terms of online help seeking [14].

In the context of an online CS course, Hakulinen and Auvinen [13] investigated students' achievement goal orientations using a person-oriented approach and identified four profiles: success (high all except for avoidance), mastery, indifferent, and avoidance.

3 METHODS

3.1 Context

The study was conducted within an open online programming course offered by the University of Helsinki during Spring 2019. The course is taught using Java and covers the basics of programming, ranging from handling standard input and output to the basics of object-oriented programming and algorithmics. The course uses an online textbook with theory, videos, program visualizations, programming assignments, and quizzes. Programming assignments are worked on within an IDE and students' work is automatically assessed using an automated assessment system that provides scaffolding and informative feedback on students' progress [37].

The course is divided into seven parts and it uses a teaching approach previously described e.g. in [36]. While most of the programming assignments in the course consist of a single small task intended for practicing a particular construct, many of the assignments scaffold students in constructing larger programs through the use of multiple tasks as a part of the problem descriptions. In total, the course has over 240 programming tasks divided over the seven parts. Each part has a set deadline, and the students are expected to complete at least 25% of the assignments in each part in order to be able to proceed to the subsequent part. If a student does not complete the minimum required assignments, they cannot continue in the course. Instead, they are offered an option to move to a course with no deadlines, giving them the opportunity to study at their own pace.

The overall workload of the course is 5 ECTS (European Credit Transfer System), which translates to approximately 135 hours of study. While the course is an open online course, it is taken by both affiliated and non-affiliated students. For affiliated students, the course counts towards degree requirements, while the non-affiliated students may receive credits of the course at their own institution, may use the course as a training for a job, or may use the course simply for the purposes of learning something new.

The course is graded based on completed programming assignments and an end-of-course exam. As the course is given online, both the exam and the assignments can be completed at a distance using a computer. The grade of the course is formed based on course assignments (50% of overall grade) and the exam (50% of the overall grade). The highest mark can be attained by collecting at least 90% of the available course points, while the minimum passing rate is 50% of the total available course points. Regardless of the grading, the student must receive at least half of the exam points to be eligible for a course grade and the course credits.

3.2 Participants and Measures

The participants were 2059 students (M_{age} = 35 years; 41.4% female) participating in an introductory programming MOOC, who completed a questionnaire assessing achievement goal orientations. The online questionnaire was administered in Spring 2019 at the beginning of the second week of the course described above. Furthermore, data from students' course assignments and exam performance were collected. Participation in the study was voluntary. Participation rate was 57.5%.

The instrument by Zingaro and Porter [42] was used for assessing students' mastery goals (3 items, e.g., "My goal is to learn as much as possible."), normative performance goals (3 items, e.g., "My aim is to perform well relative to other students."), and appearance performance goals (5 items, e.g., "One of my goals is to look smart in comparison to other students in my class."). Students rated all items on a seven-point scale ranging from 1 ("not true at all") to 7 ("completely true"). The questionnaire was translated to Finnish, which is the language used in the studied context. The Finnish translation was the same as in [41]. In addition to the achievement goal orientation survey, self reported age, and gender were used to characterize the student population.

Students' performance was measured by using 1) the points from automatically assessed programming assignments (equals to the number of correctly completed assignments), 2) the number of active weeks (when students were able to complete at least one assignment), 3) participation to the final exam, and 4) final course grade.

3.3 Data Analyses

Confirmatory factor analysis was used to validate the goal orientation questionnaire. Composite scores were computed for each of the three achievement goal orientations, and their internal consistency was evaluated by calculating their Cronbach's alpha values. Also, the correlations between all variables were examined. TwoStep cluster analysis was used to classify students into homogeneous groups according to their scores on the achievement goal orientation scales. Configural frequency analyses (CONFA) were conducted for examining how females and males, students who participated or did not participate during all weeks of the course, students who participated or did not participate in the final exam, and students who passed or did not pass the final exam were distributed in the groups. CONFA [38] compares the observed to expected frequencies in a cross-tabulation and asks whether cell frequencies are larger or smaller than could be expected based on some chance model. Types are patterns that are observed more frequently than expected by chance and antitypes are patterns that are observed less frequently than expected by chance. Furthermore, analyses of variance (ANOVA) were performed to investigate group differences in course performance. Analyses were conducted using Mplus and SPSS 25.

4 RESULTS

4.1 Preliminary Results

Factor analysis of the achievement goal items indicated that the assumed three-factor model fit the data well, χ^2 (41, N = 2120) = 315.36, p < 0.001, CFI = .984, RMSEA = .057, SRMR = .033. Error covariances between one pair of similarly worded items were freed. Descriptive statistics, Cronbach's alpha reliabilities, and correlations for all continuous variables are presented in Table 1.

4.2 RQ1: Achievement Goal Orientation Profiles

A TwoStep cluster analysis resulted in a five-cluster solution. Silhouette score .4 indicates a fair fit of the model. The achievement goal orientation profiles are visualized in Figure 1.

The profiles were labeled as Approach-Oriented[1] (N=643, 31.2%), Performance-Oriented (N=389, 18.9%), Combined Mastery and Performance Goals, N=370, 18.0%), Low Goals (N=363, 17.6%), and Mastery-Oriented (N=294, 14.3%). The differences between profiles in clustering variables were all significant, as illustrated in Table 2.

Application of CONFA (χ^2 (4, N=2016)=13.63, p=0.009) revealed that it was typical for female students to be in the Low Goals group (type) and untypical for male students to be in this group (antitype).

[1]The label is inspired by work of Senko [29], arguing that, according to the goal standards model, the 'real' performance-approach goal is the striving to outperform others (i.e., normative) and it is also the one that produces more positive effects with respect to, for example, academic achievement, compared to appearance performance goals. As approach-oriented students scored high in both mastery (i.e., mastery-approach) and normative performance (i.e., performance-approach) goals, the label approach-oriented was chosen for this group (see also [19]).

Table 1: Correlations between continuous variables, their means (M), standard deviations (SD), and Cronbach's alpha (α) for latent variables. Significance levels are reported after Holm's correction for multiple comparisons, *p<.05, **p<.01, and ***p<.001

	1.	2.	3.	4.	5.	6.	M	SD	α
1. Mastery							5.98	0.97	0.86
2. Normative perf.	0.34***						4.37	1.61	0.92
3. Appearance perf.	-0.02	0.36***					2.23	1.30	0.92
4. Points	0.06*	0.08**	0.07*				138.3	94.3	-
5. Weeks	0.05	0.07*	0.07*	0.98***			4.24	2.54	-
6. Grade	0.05	0.06*	0.05	0.62***	0.60***		1.14	2.03	-
7. Age	-0.05	-0.16***	-0.10***	-0.06	-0.05	-0.06*	35.3	12.0	-

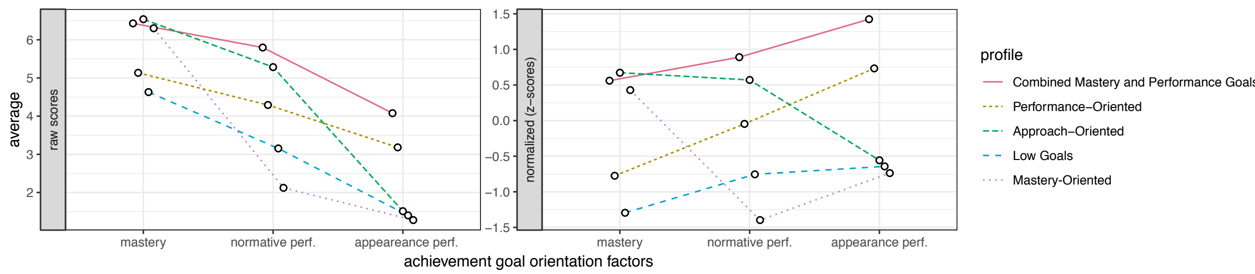

Figure 1: Achievement goal orientations (mean values) for all profiles.

Table 2: Mean values, standard deviations and one way ANOVA of achievement goal orientation dimensions between all profiles. Combined stands for the Combined Mastery and Performance Goals profile.

	Approach-Oriented		Performance-Oriented		Combined		Low Goals		Mastery-Oriented				
	M	SD	M	SD	M	SD	M	SD	M	SD	F(4,2054)	p	η^2
Mastery	6.54	0.46	5.13	0.73	6.43	0.52	4.63	0.71	6.30	0.51	894.710	< .001	.64
Normative perf.	5.28	1.07	4.29	0.94	5.80	0.90	3.15	1.08	2.12	0.84	848.371	< .001	.62
Appearance perf.	1.51	0.53	3.18	0.83	4.08	0.99	1.40	0.50	1.28	0.44	1315.407	< .001	.72

Table 3: Cross-tabulation of binary performance metrics (i.e., studying till the last week, participating exam, and getting a passed grade from the course) and achievement goal orientation profiles.

	Participated all weeks		Participated exam		Passed grade		
	FALSE	TRUE	FALSE	TRUE	FALSE	TRUE	n
Combined Mastery and Performance Goals	211 (57%)	159 (43%)	258 (69.7%)	112 (30.3%)	270 (73%)	100 (27%)	370
Performance-Oriented	228 (58.6%)	161 (41.4%)	278 (71.5%)	111 (28.5%)	289 (74.3%)	100 (25.7%)	389
Approach-Oriented	386 (60%)	257 (40%)	461 (71.7%)	182 (28.3%)	482 (75%)	161 (25%)	643
Low Goals	232 (63.9%)	131 (36.1%)	282 (77.7%)	81 (22.3%)	294 (81%)	69 (19%)	363
Mastery-Oriented	184 (62.6%)	110 (37.4%)	214 (72.8%)	80 (27.2%)	219 (74.5%)	75 (25.5%)	294

4.3 RQ2: Profile Differences in Performance

When investigating performance on a high level, CONFAs revealed equal distribution of students in the achievement goal orientation groups regarding those students who participated during all weeks of the course and those who did not (χ^2 (4, N=2059)=4.76, p=0.313), those who participated in the final exam and those who did not (χ^2 (4, N=2059)=6.75, p=0.150), and those who passed the final exam and those who did not (χ^2 (4, N=2059)=7.76, p=0.101). Distributions of these measures are provided in Table 3.

In more detailed analysis, profiles differed significantly with respect to programming assignment points, F(4,2054)=2.94, p=.019, η^2=.01. Post-hoc comparisons using the Bonferroni correction indicated that the mean score for the Combined Mastery and Performance Goals profile (M=149.03, SD=93.43) was significantly different than for the Low Goals profile (M=126.87, SD=93.00). There were no other significant differences between the profiles for this metric.

Table 4: Mean values, standard deviations and one way ANOVA of performance measures between all profiles. Combined stands for the Combined Mastery and Performance-Oriented profile.

	Approach-Oriented		Performance-Oriented		Combined		Low Goals		Mastery-Oriented				
	M	SD	M	SD	M	SD	M	SD	M	SD	F(4,2054)	p	η^2
Points	139.18	94.91	141.46	93.35	149.03a	93.43	126.87a	92.96	132.49	95.64	2.944	.019	.01
Weeks	4.24	2.54	4.36	2.54	4.51a	2.49	3.98a	2.57	4.06	2.54	2.624	.033	.01
Grade	1.16	2.05	1.18	2.04	1.29a	2.13	0.87a	1.81	1.21	2.09	2.297	.057	.00

Results for the active weeks metric were also significant, $F(4,2054) = 2.62$, p=.033, η^2=.01. Post-hoc comparisons using the Bonferroni correction indicated that the mean score for the Combined Mastery and Performance Goals profile (M=4.51, SD=2.49) was significantly different than for the Low Goals profile (M=3.98, SD=2.57). Profile differences in exam attendance were non-significant, $\chi^2(4)$=6.75, p=.150, C=.06.

Finally, achievement goal orientation profile did not significantly predict course grade, which consisted of programming points (50%) and exam grade (50%), $F(4,561)$=1.50, p=.202, η^2=.01.

5 DISCUSSION

5.1 Motivational Profiles

The objective of the present study was to identify the achievement goal orientation profiles present in a programming MOOC. Although there is already a large number of studies examining students' achievement goal orientation profiles and their associations with relevant academic outcomes, to our knowledge and based on recent literature review [24], there is no prior study using appearance and normative performance goals amongst mastery goals as the clustering variables.

We identified five distinct motivational profiles. The largest cluster, Approach-Oriented students, consisted of almost a third of the students. The profile is characterized by high mastery and normative performance goals, while appearance performance goals are low. Approach-Oriented students strive to master the content and perform well compared to other students. Mastery-Oriented students form the smallest cluster in the present sample (14%). While highly motivated by mastery, these students' scores in both performance orientations are the lowest of all profiles. Mastery-Oriented students strive to learn and master the course content but are not motivated by any normative comparisons. The remaining three clusters are students with Low Goals, students with Combined Mastery and Performance Goals and Performance-Oriented students. Performance-Oriented cluster can be characterized as seeking good performance and also appearing talented. They are separated from the Combined Mastery and Performance Goals group by a relatively weak interest to mastery. Finally, Low Goals group is characterized by relatively low scores on each of the orientations.

The number and nature of the identified profiles in the context of a programming MOOC were largely in line with prior studies conducted in different educational contexts; that is, we also found profiles characterized by predominantly mastery, predominantly performance, combined mastery and performance as well as low goals. In addition, applying the distinction into appearance and normative performance goals resulted in separating two groups of students equally striving for learning and outperforming others but differing in the goal for appearing competent; for students in the Approach-Oriented group, appearing competent was trivial, while for students in the Combined Mastery and Performance Goals group looking smart compared to peers was important. It is interesting that students in all groups scored rather high in mastery. The differentiation of appearance and normative performance goals seemed to yield meaningful motivational profiles, but further studies are still needed to establish their relevance.

Although Hakulinen and Auvinen have used a different achievement goal orientation framework, their study is closest match to us as they have applied person-oriented approach in a similar context [13]. Hakulinen and Auvinen identified four profiles: Success-Oriented (40%), Mastery-Oriented (28%), Indifferent (22%), and Avoidance-Oriented (10%). Their Success-Oriented and Mastery-Oriented profiles are similar to our Combined Mastery and Performance Goals and Mastery-Oriented profiles, correspondingly. The rest of the groups do not have clear counterparts. It's still interesting to note how the number of students with Combined Mastery and Performance Goals was clearly smaller in our case.

5.2 Performance and Goal Orientation

With regard to performance, students with Combined Mastery and Performance Goals stayed active on the course for longest and gained most programming assignment points, performing significantly better than students with Low Goals who dropped out earliest and gained less programming assignment points. Differences in performance between other profiles were non-significant.

When comparing the Combined Mastery and Performance Goals and Approach-Oriented profiles we noticed that while the mastery and normative goals go pretty much hand in hand, it is the appearance goal that distinguishes the profiles. As it turned out, Combined Mastery and Performance Goals profile, with its relatively high level of appearance goal, was the most advantageous profile in terms of academic achievement. Approach-Oriented profile, with a considerably lower level of appearance goal, did not differ from other profiles significantly.

It has been proposed that a combined mastery and performance goal profile, not a predominantly mastery-oriented profile, might serve as the most adaptive motivational pattern in terms of achievement outcomes for students in challenging and performance-focused educational contexts, such as higher education [24]. Regarding both Combined Mastery and Performance Goals and Mastery-Oriented profiles, our results seem consistent with previous studies conducted in such settings (e.g., [34, 35]). It is, however, important to note that, in the long run, striving for multiple goals (i.e., high performance goals alongside mastery) is linked not only with high achievement but also with vulnerability to emotional distress (e.g., stress, burnout [34]), which adds another viewpoint to the discussion on which orientation is good for what.

Another interesting perspective on our results is the effect of the appearance performance goal. Previous studies have shown appearance goals as negatively related or unrelated to educational outcomes [16], the latter also in CS context [41, 42]. Our findings, however, seem to not be in line with prior research, as our results show a significant positive – yet weak – correlation between the appearance goal and two performance metrics: programming assignment points and active weeks. Finally, the comparison of motivational profiles and performance is a timely topic as there is an increasing interest to use psychological measurements to predict and explain students performance also in computing education [15].

5.3 Contextual Factors

The context of the study is important to note as the goals of the students participating in a voluntary online course may differ from degree students. For example, Watted and Barak [39] observed that while degree students are oriented toward improving knowledge, non-affiliated students are interested about more specific career benefits. Despite differences in student populations, the same courses are still provided for both degree and MOOC students [21].

The findings of the present study contribute to the debate on which orientation is good for what and, more specifically, whether mastery or combined mastery and performance goals lead to better performance, in the context of a programming MOOC. In our analysis, mastery-oriented students did not stand out from the other groups. One potential explanation for this lies in the type and focus of the assignments of the course. The course uses a teaching approach that utilizes a large quantity of small assignments, which are well defined and automatically assessed. As mastery goals are often related to interest-based study strategy [30], which in turn is related to low performance in mostly closed-format exams, it is possible that another format of course assignments (e.g., small amount of large assignments) would be preferable to mastery-oriented students.

At the same time, there is evidence that smaller practice assignments support students learning the topic, and reduces the likelihood of postponing work [5]. This raises the question whether instructors taking a part of designing MOOCs should consider creating multiple versions of the course, where, on one hand, motivational profiles and, on the other hand, background and affiliation would be taken into account [17]. We argue that contextual factors might explain variation in the results related to the role of achievement goals in computing education [41], and that this should be addressed in future research.

In a broader sense, with the exception of a handful of studies (e.g., [1, 18, 40–42]), achievement goal orientations have been mostly studied outside of CS education research [24]. Acknowledging the challenges related to fitting existing frameworks and taxonomies into the CS education context [10, 20, 33], it is evident that there is a need to explore the fit of such theories to the CS education domain, in addition to the more prevalent topics (outlined e.g. in [22]).

5.4 Limitations of Work

Our study comes with a set of limitations, which we address next. First, we acknowledge sampling and selection bias due to the context of the study. The study has been conducted in a specific country and in a specific course, where students could choose whether they want to answer the questionnaire and whether they want to provide research consent. This limits the generalizability of our results, as demonstrated in the earlier work related to achievement goals in computing education [41]. Moreover, participation rate of the study was about 60%, and while we don't believe this has significant impact on the profiles per se, it is unclear how representative the proportional shares of the clusters really are.

Second, in the analysis of RQ2, we did not focus on previous programming experience due to space constraints. We acknowledge that previous programming experience often influences students' performance in introductory programming courses, and acknowledge that it is a confounding variable that influences the internal validity of our results. Third, as both the course assignments and the exam can be taken at a distance, it is possible that some students have received help as they work on the assignments while others may have not had access to such help. That is, students in the course may have had uneven access to help, which – even if their goal orientations are similar – may influence their success in the course.

6 CONCLUSIONS

In this work, we studied achievement goal orientations of over 2000 students participating in an introductory programming MOOC. While answering to our first research question, *What kinds of achievement goal orientation profiles can be identified among students participating in a programming MOOC*, we identified five distinct motivational profiles: Approach-Oriented who strive to master the topic and perform well, without a particular need to appear smart in front of others (31%), Performance-Oriented (i.e., seeking good performance and also appearing talented, 19%), Mastery-Oriented (i.e., interested in mastery, but not preoccupied with performance 14%), as well as students with Low Goals (i.e., having low scores in all of the measured motivational dimensions, 18%) and students with Combined Mastery and Performance Goals (18%). Profiles are somewhat similar to previous research, although the findings are unique as there are no prior studies using appearance and normative performance goals with mastery as the clustering variables.

Our answer to the research question 2, *Do students with different achievement goal orientation profiles differ with respect to their course performance*, indicates that although students with Combined Mastery and Performance Goals perform better than students with Low Goals, the differences are, all in all, small. In previous research, similar profiles characterized by striving for multiple goals have been related also to negative concomitants, such as stress and burnout. In our case, almost one fifth of the students were categorised as striving for multiple goals. This raises the questions of whether study material could be modified so that it would not guide towards potentially stressful study habits. Moreover, further research is needed to understand if motivational profiles between degree students and MOOC students differ also in online programming education, and whether this distinction could be used to adapt courses to different audiences.

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